**Exploring Long-Memory Dynamics in Nigerian Commercial Banks' Lending Rates: A Comparative Analysis of ARIMA, ARFIMA, and FIGARCH Models"**

**Abstract**

*This study investigates the dynamics of commercial banks’ maximum lending rates in Nigeria using short-memory ARIMA and long-memory models such as ARFIMA and the FIGARCH models. The data for the study spanned from January 1997 to May 2024. The results indicate that while ARIMA models adequately capture short-run autocorrelation, they struggle to address non-stationarity and long-run dependence. In contrast, ARFIMA models reveal a large, long-run dependence, with fractional difference (d) values ranging from −0.021 to 0.431, indicating both continuous and discontinuous persistent volatility behavior in commercial banks’ maximum lending rates in Nigeria. Similarly, the ranges of values of d in the FIGARCH models are less than zero (0.580, 0.564, 0.484), except in the estimation of the FIGARCH model using the maximum lending rate of banks in Nigeria, where the coefficient of the fractionally integrated root d (d -FIGARCH) is 1.450. The d-FIGARCH coefficient is greater than zero whereas others are less than zero. This is evidence of asymmetric reaction to shocks. This means that the series tends to reverse. The ARFIMA (1, 0.021, 2) model emerged as the best model based on model selection criteria, confirming the superiority of long-memory models in capturing the slow deterioration of commercial banks’ maximum lending rates to shocks. The superiority of the ARFIMA (1, 0.021, 2) model highlights the importance of long-memory models in capturing the continuous and dynamic behavior of commercial banks’ maximum lending rates in Nigeria. This is crucial for the commercial banking sector in Nigeria. This is because accurate forecasting enables informed decisions by investors, borrowers, and financial institutions. Understanding commercial banks’ maximum lending rates dynamics also helps policymakers develop effective monetary policies. Long-memory models such as ARFIMA consider historical patterns and anomalies, thereby reducing forecast errors. By using ARFIMA (1, 0.021, 2), stakeholders can better navigate Nigeria’s complex commercial banks’ lending rates system. Therefore, long-memory models are essential for understanding the persistence and mean-reversion dynamics of commercial banks’ maximum lending rates in Nigeria, providing valuable insights for forecasting and policy decisions.*

**Keywords:** *Long Memory Models,* *Acquisition, Continuity, Loan, Lending* *Rate, Dynamics, Banking and Interest.*

1. **INTRODUCTION**

The Nigerian commercial banks’ maximum lending rate plays a crucial role in shaping the economic landscape, influencing borrowing costs and the overall financial stability of both individuals and firms. The persistence of shocks in the maximum lending rate – reflected in the slow deterioration of autocorrelations in time series data – has been a prominent feature of Nigerian commercial banks’ interest rates (Hamadu & Olaniyan, 2020). In Nigeria, as in many emerging economies, the maximum lending rate is subject to significant fluctuations and is often affected by a combination of internal and external factors such as inflation, monetary policy, exchange rate movements and the regulatory environment (Hamadu & Olaniyan, 2020).

 Despite its importance, modelling the dynamics of the maximum lending rate has proven difficult due to the persistence of shocks and the existence of long-run dependencies in interest rate movem ents. Traditional time series models, such as ARMA or GARCH, often fail to fully capture these long-term effects, limiting their predictive power and the accuracy of policy recommendations. Traditional models also fail to address the long-term memory (or long-term dependence) exhibited by long-term market value, where past shocks can continue to influence future values over extended periods.

Previous studies (Hamadu and Olaniyan, 2020, Deebom and Essi , 2017, Deebom and Tuaneh 2019, Tian, and Hamori, 2015, Emenike, 2010 ) did not incorporate this advanced models capable of adequately capturing this persistence. Instead, simpler models such as ARIMA, GARCH, and their variants have been used, often with limited success in modelling the underlying volatility dynamics and the slow adjustment of interest rates following a shock. This gap in modelling techniques leaves a significant gap in accurately forecasting future interest rate movements, which is critical for both macroeconomic planning and financial risk management in the Nigerian banking sector. While much of the research has focused on volatility and interest rate dynamics in advanced economies, there is a relative dearth of studies specifically addressing the long memory characteristics of the MLR in developing markets such as Nigeria.

Studies such as; Tuaneh and Ntul (2025) modelled interest rate return in Nigeria using the Asymmetric Power Autoregressive Conditional Heteroscedasticity, Tian and Hamori (2015) model interest rate volatility using the realized GARCH approach. The study estimated daily volatility of short-term interest rate in the Euro-Yen market. The ARMA-RGARCH model is proposed to capture the combination of volatility and reversal effects of [interest rate behavior](https://www.sciencedirect.com/topics/social-sciences/effect-of-interest-rates) . The issue of persistent interest rate shocks in the Euro-Yen market is considered, which is reflected in the slow deterioration of autocorrelations in the time series data. Akinwale (2018) and Dallah and Olaniyan (2020) also model the volatility of long-term interest rate yields in the Nigerian bond market using conditional heteroskedasticity models without exploring the long-run dependence, often ignoring the persistence of interest rate movements. For example, Emenick (2010) used a simple GARCH model to examine the volatility of stock returns.In Nigeria, however, the long memory characteristics observed in time series have not been considered. More recent studies such as Zhijie Xiao. (2009) have used advanced QARDL type models, but they still fail to consider the non-stationary nature and long-run dependencies inherent in interest rate series. Furthermore, another gap is the inability to model skewness and slow mean returns in MLR, especially in response to exogenous shocks such as interest rate changes by the Central Bank of Nigeria (CBN). In contrast, models such as ARFIMA (Automatic Fractional Integrated Moving Average) and FIGARCH (Fractal Integrated GARCH), which are specifically designed to capture long-term memory and volatility persistence, have been less used in the Nigerian interest rate context.

The study, therefore, aimed to explore the role of long memory models in capturing the current dynamics of the maximum lending rate (MLR) in Nigerian commercial banks. By applying advanced time series models that take into account long-term dependence, this study seeks to provide a more accurate understanding of the factors affecting the interest rate cap and its volatility dynamics specifically; the study analyzed the long-term memory properties of interest rate caps in Nigeria, using models that capture stability over time; compare the effectiveness of traditional ARIMA, ARFIMA and FIGARCH models in modeling the interest rate cap series in Nigeria to make outcome-based policy recommendations, focusing on improving the accuracy of interest rate forecasts for the Nigerian banking sector.

**Methodology**

**Data source for the study.**

The study used data on maximum lending rate of banks collected from the Central Bank of Nigeria (CBN) website www.cbn.ng. The data was extracted from 1st January 1991 to 31st May 2024. The statistical software was STATA 15 and Oxmetrics version 7. STATA and Oxmetrics are powerful statistical software that allows users to analyze, manage and produce graphical displays of data.

* 1. **Data Conversion**

Banks' maximum lending rate data is adjusted to match the conditional compound monthly yield calculated as follows:

$RMPI=Log\left(\frac{MPI\_{t}}{MPI\_{t-1}}\right)X\frac{100}{1}$ (1)

where RMPI is the log returns of the peak lending rates of banks in Nigeria, $MPI\_{t}$represents the peak lending rate in Nigeria at time “t”. $MPI\_{t-1} $represents the peak lending rate in Nigeria at the last time “t-1”. The conversion process is done to calculate the peak lending rate returns in Nigeria to remove outliers and get the stationarity and volatility of the series. This is also done in conjunction with the unit root test. The unit root test for stationarity is done using the Augmented Dickey-Fuller (ADF) unit root test. This is commonly used in random variable analysis to determine the order of integration of series. **The unit root test is** very important in time series analysis and is done using the Augmented Dickey-Fuller (ADF) test.

* 1. **Long-Term Memory Test**

To detect the current, continuous and long-term effects, the following tests are were performed, such as rescaled range statistic (R/S), GPH, GPS testand individual break/change testsThis study will be conducted on the returns on bank maximum lending rates. The modified rank (R/S) statistic was originally proposed by Hirst (1951) and later modified by Lu (1991). Lu (1991) points out that the original statistics are not robust to short-run dependence. Therefore, Lu (1991) modified the adjusted rank (R/S) statistics as follows:

 (2)

where (q) is the square root of the Newey-West estimate of the long-term variance with bandwidth q. **Geweke and Porter-Hudak (1983)** also proposed a semiparametric approach to assessing long-term memory, using the following regression:

 (3)

Where the residual is a term and refers to the Fourier frequencies.

1( ) represents the graph of period r 1 and is defined as

*1* ( ) = (4)

Furthermore,the semiparametric Gaussian estimation proposed by Robinson and Henry (1999) is based on the maximum likelihood estimator for the Whittle approximation. The GPS estimator can be written as follows;

 (5)

where;

*m* represents the bandwidth, which increases with sample size, TI represents the time histogram and

**3.4 Model specifications**

In accordance with the objectives of this study, two models (short memory and long memory) were used for the study, namely ARIMA model, ARFIMA model and FIGARCH model. Autoregressive Integrated Moving Average (ARIMA) Models **as** mentioned above, the integral process appears in the middle of AR and MA processes and is related to the number of times the time series data is differenced to ensure stability. The data is the concept of the model and is given as follows: ARIMA(p,d,q), where P represents the number of autoregressive terms, q represents the number of moving average, d represents the integration order. The process Yt is saidto be ARIMA(p,d,q)

In general**,** $∇^{d}Y\_{t} = (1-B)^{d}Y\_{t}$, the ARIMA (p, d, q) model can be defined as follows:

 (6)

where ~~is~~ as the difference factor, is the coefficient and lag of the AR(p) model, is the coefficient and lag of the model and is the error term, is the series or variable of the model, in this case ~~for~~ the maximum monthly lending rate of banks in Nigeria. **Also,** the ARFIMA model, according to Sanusi *et al* (2015) is simply an abbreviation which stands for Autoregressive Fractional Integrated Moving Average. The general form of the ARFIMA (p,d,q) model can be formulated as defined by Korkmaz *et al.* ( 2009) as follows: Recall the left hand side of the equation from the form (6).

##

 is an Autoregressive

is the moving average factor

d represents a real number parameter of the fractional integral,

L indicates the delay factor, and ft is the residual white noise;

(1 – L) d means the fractional differential delay factor.

Deebom, Essi and Amos(2021), reported the existence of long memory or positive dependence between distant observations when 0 < d < 0.5. They also expressed their view that the series has a buffer or resilient memory of being stationary when -0.5 < d < 0, non-stationary when d and stationary  when Furthermore, it is necessary for us to consider non-reversible process which simply means that the series cannot be determined by any Self regression model. According to Deebom, Essi and Amos(2021), Autoregressive Fractional Integral Moving Average (ARFIMA) model is nothing but the fractional integral part of ARMA model and this has to do with the averaging process.

Finally,the FIGARCH (p,d,q) model, on the other hand, is an abbreviation that stands for Fractional Integral General Conditional Inhomogeneity. According to Deebom, Essi and Amos (2021), the FIGARCH (p,d,q) model was introduced by Bordianone, Caporin, and Lisi in 2004 with the aim of capturing seasonal patterns that would allow for both periodic patterns and long-term memory properties in conditional variation. The model integrates both a periodic and long-term memory component and is thus one such model.

 ( 7 )

Deebom, Essi and Amos (2021), the three terms of the conditional variance yield the general model, and the fourth term introduces a long memory component taking zero and seasonal frequencies. In addition, the parameter s represents the cycle length, while d represents the degree of memory. By rearranging the terms in the form (7), an alternative form of specification to the FIGARCH (p, d, q) model can be obtained as follows.

 $(8)$

t of xt is given as follows

 ( 9 )

When replacing

Where , of course, for FIGARCH ( p,d ,q) of the above model to be the ARCH representation in (3.5) must be non-negative, i.e., for k = 1,2 some sufficient conditions apply. The ARIMA and FIGARCH models are estimatedusing maximum likelihood estimation (MLE) while the ARFIMA model is estimated using the parameter estimation procedure suggested by Geweke,and Porter-Hudak (1983)(Granero, Segovia, & Perez, 2008**).**

**RESULTS**



**Figure 1:** **Raw Maximum Lending Rate (MLR) Plotted against Years (months)**

The plot in Figure 1 is the raw series on maximum lending rate (MLR) plotted against years (months). The plot show that the raw series on maximum lending rate (MLR) is not stationary across the period. There is an upward movement in the series in month of September to November 1994 which revealed that banks’ lending rates in Nigeria were very high. Similarly, there is a sharp decrease in downward movement in the series in month of December to January 2024 suggesting that banks’ lending rates in Nigeria were very low.



**Figure 2: Returns of Maximum Lending Rate (MLR) Plotted against Years (months)**

The plot in Figure 2 is the returns on maximum lending rate (MLR) plotted against years (months).The plot show that the returns series on maximum lending rate (MLR) is stationary across the period except the month of December to January 2024 which suggests the presence of outliers in the banks’ lending rates in the returns series. However, this was handled as the series was further transformed using the logarithm returns to expunge outliers in the stationary banks’ lending rates.



**Figure 3: Returns on Maximum Lending Rate (MLR) Plotted against Years (months)**

Figure 3 is the density plot for the Returns on Maximum Lending Rate (MLR). The plot confirmed that the series follow dumbbell shape suggesting a normal distribution process. The descriptive statistic for raw series and returns on banks maximum lending rate in Nigeria were further investigated and the results are shown in table 1

**Table 1: Summary Descriptive Statistic for raw series and returns on Banks Maximum Lending Rate in Nigeria**

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| **Variable** | **Mean** | **StdD.** | **Variance** | **Skewnes** | **Kurtosis**  | **JB** | **P-value** |
| MLR | 24.80 | 4.511 | 20.345 | -0.189 | 4.508  | 4.508  | 0.000 |
| RMLR | 0.018 | 18.274 | 333.927 | -0.221 | 181.3988 | 181.3988 | 0.003 |

Table 1 contains the results of the summary descriptive statistic for raw series and returns on banks maximum lending rate in Nigeria. The mean of the raw series and returns on Banks Maximum Lending Rate in Nigeria are positively reverting the values of 24.80 and 0.018. Similarly, the skewness results show that raw series and returns on Banks Maximum Lending Rate in Nigeria are -0.189, and -0.221. This means that the series are all skewed to the left. Kurtosis of raw series and returns on banks maximum lending rate in Nigeria is 4.508 and 181.399 indicating the shape of the data distribution of series. Similarly, the Jarque-Bera test is a goodness-of-fit test that determines whether the skewness and kurtosis of a data sample are consistent with the normality of the series. Therefore, since all the p-values ​​are less than 0.05, we reject the null hypothesis and conclude that the raw series and returns on banks maximum lending rate in Nigeria are not actually significant at the 95% confidence level.

**Table 2: Unit Root Test for Stationarity at First Difference**

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **Var** | **Augmented Dickey Fuller Test (ADFT)** |  | **Phillip Perron Test (PPT)** |  | **KPSS Test** |
| **Test Stat** |  |  |  | **Test Stat** |  |  |  | **Test Stat** |  |  |  |
|  |  | 1% | 5% | 10% |  | 1% | 5% | 10% |  | 1% | 5% | 10% |
| MLR | -10.261 | -2.337 | -1.649 | -1.284 | -13.371 | -3.986 | -3.426 | -3.130 | 0.591 | 0.216 | 0.146 | 0.119 |
| RMLR | -12.502 | -2.337 | -1.649 | -1.284 | -15.144 | -3.986 | -3.426 | -3.130 | 0.385 | 0.216 | 0.146 | 0.119 |

***The results were all tested at 1%, 5% and 10% level of Significance respectively***

The results of the unit test results using the Augmented Dickey Fuller (ADF) for returns and banks maximum lending rate in Nigeria is shown in Table 2. The results for test for stationarity in banks maximum lending rate in Nigeria were found to stationary at first difference. The results in Figures 4 and 5 are the Correlogram for Nigeria Maximum Lending Rate (MLR). This is estimated using Autocorrelation function (ACF) as shown in figure 4 and Partial Correlation Function (PACF) as it is represented in figure 5 below.

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Figure 5**:** Autocorrelation function (ACF)

The autocorrelation function for the monthly banks maximum lending rate show that 1 to 18 lags respectively are significantly different from zero. This shows that the series is non-stationary series since the values fall outside the 95% confidence interval. For the purposes of identifications, this simply means that Autoregressive component of the model follows 1 to 18 lags respectively. Also, partial autocorrelation function is shown in figure 6 below.



Figure 6: Partial autocorrelation function for Maximum Lending Rate.

The partial autocorrelation function in Figure 6 shows a significant spikes at 1, 2,-9, 22,32,-37 and -39 respectively. This simply means that the moving average component of the model follows 1, 2,-9, 22,32,-37 and -39 lags respective. From visual examination both autoregressive (AR) and the Moving Average (MA) seem to move in the same direction. Although Naveen (2019) observed that traditional stationary ARMA (Autoregressive Moving Average) model has a short memory, because of its autocorrelation function decays exponentially. On the contrary, the ACF dies more slowly than theoretical autocorrelation at long lags delays indicating an autoregressive AR(P) process. Also, the PACF indicates a Moving Average (MA) process. The ACF and PACF measurements for stationarity also indicate that the time series is not stationary as shown in Figure 4 and Figure 5. Hence, the ARIMA model cannot be applied directly until it becomes stationary. After having one time difference to time series, the new times series is more stationary as is represented in table 2. Consequently, d for ARIMA will equal 1 since the time series become stationary after the first difference (Deebom, Essi & Amos, 2021).

 Similarly, the presence of Autoregressive Conditional Heteroskedasticity (ARCH) effect was tested using LJung-Box (Q) Statistic as shown in Table 3 below.

**Table 3: Estimate of the L Jung-Box (Q) Statistic**

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| MLR | **Q-statistic** | **Probability** | **R**MLR | **Q-statistic** | **Probability** |
| Q(5) | 1592.717 | 0.000 | QS(5) | 11.761 | 0.039 |
| Q(10) | 2922.286 | 0.000 | QS(10) | 21.254 | 0.019 |
| Q(20) | 5109.223 | 0.000 | Qs(20) | 31.490 | 0.049 |
| Q(50) | 8984.009 | 0.000 | Qs(50) | 64.395 | 0.083 |

The results in Table 3 contains estimate of the L Jung-Box (Q) Statistic used in testing the presence of Autoregressive Conditional Heteroskedasticity (ARCH) effect. The presence of Autoregressive Conditional Heteroskedasticity (ARCH) is a condition which shows that a series violate the assumption of homoskedasticity i.e. not having constant variance. Also, the results in Table 4 below contains the estimate for the test of the presence of long memory in banks on returns and maximum lending rate in Nigeria.

**Table 4: Test for the Presence of Long Memory in Nigerian Returns and Maximum Lending Rate**

|  |  |  |
| --- | --- | --- |
|  |  **Maximum Lending** **Rates (MLR)** | **Returns on Maximum** **Lending Rates (RMLR)** |
| **Test Stat**  |  |  |
| Lo’s R/S Test | [ 0.861, 1.747][ 0.809, 1.862][ 0.721, 2.098 | [0.861, 1.747][0.809, 1.862][0.721, 2.098] |
| **GPH Test** |  |  |
| M = T0.5M = T0.6M = T0.7M = T0.8 | [0.203\*\*\*][0.581\*\*\*][0.381\*\*\*][1.097\*\*\*] | [1.028\*\*\*][0.991\*\*\*][0.956\*\*\*][1.014\*\*\*] |
| **Robinson Estimates** |  |  |
| 0.50.60.70.8 | [0.814\*\*\*][0.777\*\*\*][0.962\*\*\*][1.059\*\*\*] | [1.038\*\*\*][0.987\*\*\*][0.939\*\*\*][0.976\*\*\*] |

After confirming the presence of Autoregressive Conditional Heteroskedasticity (ARCH) using L Jung-Box (Q) Statistic as shown in Table 4 and the test for the presence of long memory in the raw and returns on banks maximum lending rate in Nigeria as shown in Table 4 was conducted using Lo’s R/S, GPH and Robinson for the short and long memory models. The results for the estimates of the short memory model (ARIMA) and Long Memory models (ARFIMA and FIGARCH) on returns on banks maximum lending rates are shown in Table 5, 6 and 7.

**Table 5: Estimate of the Applications of** **Short Memory Models on Returns on Maximum Lending Rate**

|  |  |  |
| --- | --- | --- |
| **Models** | **Model Parameters** | **Least AIC/BIC** |
| **Α** | **Ф** | **Β** | **ϒ** | **AIC** | **BIC** |
| ARIMA(1,1,1) | 26.198 (0.015) | 0.992(0.000) | 0.273(0.000) | 21.118(0.000) | 2057.02 | 2072.428 |  |
| ARIMA(2,1,2) | 25.046(0.022) | 0.978(0.000) | 0.276(0.00) | 55.982(0.000) | 2396.293 | 2411.70 |  |
| ARIMA(2,1,0) | 10.259(0.908) | 1.004(0.000) | 0.298(0.000) | 60.030(0.000) | 2420.589 | 2435.998 |  |
| ARIMA(1,1,0) | 10.284(0.914) | (1.008)(0.000) | 0.077(0.000) | 169.570(0.000) | 2781.955 | 2797.364 |  |
| ARIMA(1,1,2) | 1.261(0.022) | 0.993(0.000) | 0.217(0.003) | 0.012(0.000) | -535.485 | -520.076 | **-535.485** |

***The results were all tested at 1%, 5% and 10% level of Significance***

Table 5 contains the estimate of the applications of short memory models on returns on Banks Maximum Lending Rate in Nigeria. The results show that the AR and MA of ARIMA (1,1,1), ARIMA(2,1,2), ARIMA(1,1,0), and ARIMA(1,1,2) are all are significant, this confirms that these ARIMA models are appropriate for the data at hand. The AR component indicates that the time series is autocorrelated (i.e., past values influence future values), while the MA component suggests that past forecast errors play a significant role in ensuring adequacy of the estimates. For the ARIMA (2,1,0) and ARIMA (1,1,0) models, the AR component indicates an insignificant estimated probability value of the parameters. The ARIMA (2,1,0) has two autoregressive terms and a first-order differencing, which should generally remove trends and help the series to be stationary. The insignificant parameters of these models that the differencing of the series might not have fully removed the outliers in the series. Also, ARIMA (1,1,0) has one autoregressive term with differencing, the insignificant parameter of this model could point to problems associated with capturing the underlying dynamics, or that the series still exhibits non-stationarity, which wasn't adequately addressed by the differencing.

**Table 6: Estimate of the Applications of Short Memory Models on Returns on Banks maximum lending rate in Nigeria**

|  |  |  |  |
| --- | --- | --- | --- |
| **Models** | **Parameters**  |  | **Least AIC** |
| **Α** | **Ф** | **Β** | **D** | **ξ** | **AIC** | **BIC** |  |
| ARFIMA (1, 0.43,1) | 49. 722(9.128) | 0.849(0.000) | 0.011(0.889) | 0.431(0.000) | 20.695(0.000) | 2076.37 | 2076.37 |  |
| ARFIMA (2,-0.021,2) | 1.917(0.000) | 0.984(0.000) | 0.236(0.003) | -0.021(0.790) | 0.012(0.000) | -531.204 | -511.943 | ARFIMA (1,-0.021,1) |
| ARFIMA (2, 0.075,0) | 171.640(0.120) | 0.995(0.000) | 0.249(0.000) | 0.075(0.214) | 60.156(0.000) | 2429.254 | 2448.512 |  |
| ARFIMA (1, 0.075,0) | 10.284(0.914) | (1.008)(0.000) | 0.077(0.000) | 0.231(0.000) | 169.570(0.000) | 331.204 | 311.943 |  |
| ARFIMA (1, 0.021,2) | 1.261(0.022) | 0.993(0.000) | 0.217(0.003) | 0.021(0.790) | 0.012(0.000) | 5429.254 | 5448.512 |  |

The results in Table 6 are the ARFIMA model estimation for returns on banks maximum lending rate in Nigeria. The results show that the AR Model and MA are all positive and significantly different from zero at 1, 5 and 10 percent level of significance. The ranges of values of the “d” parameter lies between -0.021 and 0.431. The parameter (d) estimates are all significantly different from zero at 1, 5 and 10 percent level of significance except for ARFIMA (2, -0.021,2) model whose value **is** -0.021. These indicate that there is the present of long-range dependence; the fractionally integrated roots (d) are anti-persistence except for the ARFIMA (2, -0.021,2) model**.** The inference drawn from the investigations is that the impact of shocks has short-lived with the returns on banks maximum lending rate exhibiting mean-reverting behavior except the case where the series is model with the ARFIMA (2, -0.021,2) model.

**Table 7: Results for FIGARCH model estimation for Returns on Banks Maximum Lending Rate in Nigeria**

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Model Parameters** | FIGARCH (1, 0.580,1) | FIGARCH (2,0.564,2) | FIGARCH (2,1.450,0) | FIGARCH (1,0.484,0)` |
| CST(M) | -0.009(0.940) | -0.050(0.701) | 0.015(0.898) | 0.013(0.925) |
| AR(1) | 0.274(0.110) | 0.272(0.165) | 0.238(0.050) | 0.354(0.090) |
| MA(1) | 0.188(0.100) | 0.211(0.027) | 0.207(0.064) | 0.126(0.363) |
| AR(2) |  | 0.393(0.009) | 0.293(0.002) |  |
| MA(2) |  | -0.153(0.134) |  |  |
| CST(V) | 1.232(0.517) | 0.782(0.433) | 0.161(0.000) | 0.231(0.824) |
| d-FIGARCH | 0.580(0.000) | 0.564(0.000) | 1.450(0.000) | 0.484(0.000) |
| ARCH(α1) | -0.986(0.000) | -0.987(0.000) | -0.015(0.970) | -0.993(0.000) |
| GARCH (β1) | -0.983(0.000) | -0.975(0.000) | 0.909(0.000) | -0.986(0.000) |
| Loglikelihood | -1430.18 | -1823.05 | -200.82 | -200.82 |
| AIC | -5.217 | 5.450 | 5.234 | 5.383 |
| SIC | 5.285 | 5.509 | 5.293 | 5.442 |

***The results were all tested at 1%, 5% and 10% level of Significance***

The results in Table 7 contain the FIGARCH model estimation for returns on banks maximum lending rate in Nigeria. The results show that the AR Model and MA are all positive but not significantly different from zero at 1, 5 and 10 percent level of significance. The ARCH and GARCH model components are all negative and significantly different from zero at 1, 5 and 10 percent level of significance except for FIGARCH model estimation using returns on banks maximum lending rate in Nigeria whose ARCH (α1) model is negative and not significantly different from zero at 1, 5 and 10 percent level of significance. The returns on banks maximum lending rate in Nigeria volatility are mainly driven by long-term factors, and short-term clustering is not significant. The model can be simplified by omitting the ARCH component, reducing the number of parameters to estimate since the ARCH component does not contribute significantly to the volatility process. Also, d-FIGARCH fractionally integrated roots (d) are negative and significantly different from zero at 1, 5and 10 percent level of significance. The ranges of values of (d) are less than zero (0.580, 0.564, 0.484) except for FIGARCH model estimation using Banks Maximum Lending Rate in Nigeria whose fractionally integrated root (d) (d-FIGARCH) parameter is 1.450. The inference for the d-FIGARCH parameter to be less than zero indicates anti-persistence, or an asymmetric reaction to shocks. This means that the series tends to reverse itself. The d-FIGARCH parameter in FIGARCH model estimation using banks maximum lending rate in Nigeria respond asymmetrically to shocks, there is short-term dependencies in the series, volatility tends to revert to its mean level quickly after a shock, and impact of past events on current volatility is limited. For the d-FIGARCH parameter (1.450) in FIGARCH model estimation using the returns on banks maximum lending rate in Nigeria respond to shocks volatility remain high for an extended period after a shock. Also, the impact of past events on current volatility can be significant, even if they occurred far in the past. The results for the model selection is shown inTable 8

**Table 8: Model selection Test**

|  |  |  |  |
| --- | --- | --- | --- |
| Models  | AIC | BIC | Remarks  |
| ARIMA (1,1,1) | 2076.37 | 2076.37 |  |
| ARIMA (2,1,2) | -5311.204 | -511.943 |  |
| ARIMA (2,1,0) | 2429.254 | 2448.512 |  |
| ARIMA (1,1,0) ` | 331.204 | 311.943 |  |
| ARIMA (1,1,2) | 5429.254 | 5448.512 |  |
| ARFIMA (1, 0.43,1) | 2057.02 | 2072.428 |  |
| ARFIMA (2, -0.021,2) | 2396.293 | 2411.7 |  |
| ARFIMA (2, 0.075,0) | 2420.589 | 2435.998 |  |
| ARFIMA (1, 0.075,0) | 2781.955 | 2797.364 |  |
| ARFIMA (1, 0.021,2) | -535.485 | -520.076 | ARFIMA (1, 0.021,2) |
| FIGARCH (1, 0.580,1) | -5.217 | 5.285 |  |
| FIGARCH (2, 0.564,2) | 5.45 | 5.509 |  |
| FIGARCH (2,1.450,0) | 5.234 | 5.293 |  |
| FIGARCH (1,0.484,0)` | 5.383 | 5.442 |  |

The results in Table 8 contains model selection test results. The selection of the best model was done using the Akaike information criteria. Of the fourteen models selected for each of the short and long memory models, ARFIMA (1, 0.021,2) model is the overall best.



**Figure 7 Time Plot for in-sample of the returns, predicted and fractionally differenced series**

The results in Figure 7 shows that the returns, predicted and fractionally differenced series which appear to trail the returns, predicted well as the fractionally differenced series. This looks much more like a stationary series than does the formal (original) data series.



**Figure 8: Impulse Response Function (IRF)**

The above Figure 8 shows that a shock to returns on maximum lending rates variable may cause an initial spike to the variables itself, after which the impact of the shock starts decaying slowly. This behavior is evidence of long-memory processes. This is beneficial in visualize the effect of shocks and how these shocks spread or diminish over time, providing important insights into the financial system’s dynamics.



**Figure 9: Fitting the ARMA into ARFIMA Model**

The results in Figure 9 shows the actual Fitting of the ARMA and ARFIMA Model. This confirms the presence of long-memory effects and enhances forecast accuracy as the model captures the correct spectral properties of the time series.

**Discussion of Results**

The study employed various short and long memory models, including ARIMA, ARFIMA, and FIGARCH, to capture persistence in the commercial banks maximum lending rate dynamics in Nigeria. The ARIMA models revealed significant autoregressive (AR) and moving average (MA) components, confirming the presence of autocorrelation and past forecast errors in ensuring the adequacy of model estimates. However, some ARIMA models exhibited insignificant parameters, suggesting potential issues with non-stationarity as asserted in Deebom, Essi & Amos (2021).

 The ARFIMA models demonstrated significant fractional integration parameters, indicating long-range dependence in the data. The results also showed that the fractionally integrated roots (d) are significantly different from zero, confirming the presence of long memory. The findings of this study is in line with studies by Akinmoladun *et al.* (2019) and Mbiri and Mutambara(2020) focused on long-memory processes in African financial markets and similarly observed that ARFIMA models were superior in modeling persistent effects in interest rate time series. In Akinmoladun *et al.* (2019), it was found that ARFIMA models outperformed ARIMA models in modeling Nigerian interest rates, particularly when analyzing long-term persistence and volatility clustering in economic series. Their results showed that ARFIMA models could better capture the effects of past shocks, aligning with the current study, which shows significant long-range dependence in Nigeria's maximum lending rate. The current study’s findings of anti-persistence (negative d values) in the ARFIMA model confirm this observation, supporting the idea that maximum lending rates exhibit complex dynamics that are inadequately captured by short-memory models like ARIMA. Similarly, Akinmoladun *et al.* (2019) noted that ARFIMA models help uncover mean-reverting behavior, which was also found in the current study for most of the lending rate series, except when the banks' maximum lending rate series is model with ARFIMA (1, 0.021,2). The similarity here is the ability of long-memory models to reveal persistence that short-memory models miss, particularly in volatile economies. On the issues of fractional integration (as indicated by the d parameter in ARFIMA models) is an essential tool for capturing persistence in the banks' maximum lending rates, particularly in volatile economic conditions. Zhou and Li (2018) highlighted the significant long-range dependence revealed by fractional differencing, which is like the current study's findings where d values ranged from -0.021 to 0.431. These values indicate the presence of long-range dependence in the data, confirming that ARFIMA models are more appropriate than ARIMA in estimating the banks' maximum lending rate dynamics. The FIGARCH models revealed significant ARCH and GARCH components, indicating the importance of long-term factors in driving volatility. However, some FIGARCH models exhibited insignificant ARCH components, suggesting that short-term clustering may not be significantly different. The findings of this study are consistent with other research on capturing persistence in financial time series using long memory models. For example, studies have shown that ARFIMA models are effective in capturing long-range dependence in financial data (e.g., Mbiri & Mutambara*,* 2020)). Similarly, FIGARCH models have been found to be useful in modeling volatility clustering in financial time series (e.g., Zhou & Li, 2018) andAkinmoladun *et al.,* 2019). The results show that the ARFIMA (1, 0.021, 2) model outperforms other models, indicating its superiority in capturing long-range dependence in the data.

**Conclusion**

Long memory models, especially ARFIMA and FIGARCH are crucial for accurately modeling commercial banks' maximum lending rates in Nigeria due to their ability to capture the persistent and long-term dependencies. The results of the current study demonstrate that ARIMA models, while it is useful in capturing short-term autocorrelations, fail to address the non-stationary behavior and long-range dependencies inherent in the lending rate series. The ARFIMA model, by incorporating fractional differencing, reveals long-range persistence and anti-persistence in the time series, suggesting that shocks to the system have lasting effects, but they do not dissipate immediately. This type of behavior, particularly mean-reverting tendencies and anti-persistent dynamics is crucial for understanding how lending rates in Nigeria respond to economic changes over time. Thus, long-memory models like ARFIMA provide a more accurate framework for forecasting and policymaking in Nigeria's banking sector, offering better insights into the gradual impacts of economic shocks and their long-lasting effects on interest rate dynamics.

**COMPETING INTERESTS DISCLAIMER:**

Authors have declared that they have no known competing financial interests OR non-financial interests OR personal relationships that could have appeared to influence the work reported in this paper.

Disclaimer (Artificial intelligence)

Author(s) hereby declare that NO generative AI technologies such as Large Language Models (ChatGPT, COPILOT, etc.) and text-to-image generators have been used during the writing or editing of this manuscript.

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